Introduction to Social Data Science

Group 16, Exam Numbers: 46, 93, 186 & 229

Building an IKEA Index

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Contributions

Sections	Exam No.
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1 Introduction

The Economist's Big Mac Index is an indicator for purchasing power differentials that according to the Purchasing Power Parity (PPP), will be equalized by currency valuations in the long run. The index is meant to predict currency mismatches that allow making profits through arbitrage.

The PPP theory relies on the assumption that the price-income relationship is monotonically increasing for cross-sectional comparisons of countries. Using GDP as a proxy for purchasing power would therefore be justified.

In this paper, we build an "IKEA Index" from scraped data. We obtain this data by scraping as many IKEA websites as possible and obtaining the price for each product. The final amount of goods and prices we obtain is 98 593 throughout 40 countries. From this, we build a product-specific index for one of the products present in most countries (KLÄMTARE) and compare it to the Big Mac Index to see which one matches better with GDP per capita. We then build indices for a big sample of products across various categories in each country and from them compute the IKEA Index for each country.

We conclude that the Big Mac Index matches better with GDP per capita, but that the IKEA Index performs very similar in countries within the European Single Market (ESM). Non-ESM countries seem to have a negative though the insignificant correlation between GDP per capita and the IKEA Index. These findings support those in Hassan 2016, where he concludes that price-income relationships are non-positive for developing countries, in which the gap between the PPP and the market exchange rate is high (Callen 2007). Moreover, countries within the ESM are not subject to tariffs or restrictions on trading, displaying a significant positively sloped relationship between IKEA Index and GDP.

We will explore the IKEA data, and examine whether IKEA prices is a good indicator for PPP and general price levels in countries.

1.1 Short Literature Review

Our index is inspired by The Economist Big Mac Index model[1]. They collect prices of Big Macs from all over the world and compute an index to see whether currencies are over- or undervalued.

Another example of a similar index is the KFC Index,[2] which also uses a single product to compare prices. The KFC Index is solely used in African countries to fill in the gaps of the Big Mac Index. The Swiss bank UBS collects a basket of goods for cities around the world. It is an expanded version of the Big Mac Index, and collects several prices for multiple categories[3]. The UBS and Big Mac indices show some of the same patterns to our index, with higher price levels in Switzerland, Norway and the US and lower price levels in countries in Eastern Europe.

The relationship between PPP and exchange rates is discussed in Balassa 1964,where he states that there is a linear relationship between Gross National Product and PPP. However, Hassan 2016 discusses this relationship as-well and suggest that the relationship between income and prices is non-positive for developing countries.

[1]https://www.economist.com/news/2020/07/15/the-big-mac-index
[2]http://www.sagaciresearch.com/kfcindex/
[3]https://www.ubs.com/microsites/prices-earnings/en/explore/

2 Data Collection

2.1 Obtaining the Information needed for Website Scraping

Our sources of data are the English Wikipedia page and websites of multiple IKEA franchisees. The data used for the design of the indices is owned by one or more of the different IKEA entities that hold the copyright.

Since we want to scrape the prices from as many countries as possible we first need to get a list of countries with IKEA stores. The best list would be one that not only gives us the countries but also the individual holdings. IKEA has a franchise model, where the company that owns the intellectual property does not operate any stores. Most IKEA stores are within the European Single Market(ESM) and most of these stores are owned by INGKA Holding. This holding company owns close to 90 percent of all stores worldwide and the rest are owned by other franchisees.[4] We use a list containing this information from Wikipedia and scrape it.[5]

Table 1: List of Countries with IKEA

Countries	**Holding**
Egypt, Qatar, United Arab Emirates	Al-Futtaim Group
Kuwait, Morocco, Jordan	Al-Homaizi Group
Bahrain, Saudi Arabia	Al-Sulaiman
Hong Kong, Indonesia (as Hero Supermarket) Taiwan	Dairy Farm
Bulgaria, Cyprus, Greece	House Market Group
Malaysia, Singapore, Thailand	Ikano
Australia, Austria, Belgium, Canada, China Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, India, Ireland, Italy, Japan, the Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, South Korea, Spain, Sweden, Switzerland, United Kingdom, United States	INGKA Holding
Turkey	Mapa
Iceland, Latvia, Lithuania	Miklatorg Group
Israel	Northern Birch
Dominican Republic, Spanish Islands	Sarton Group

After transforming the list, so that we just have one country per row but keeps the corresponding holdings, it is ready to be used to obtain all the information we need.

To scrape the websites we need to construct the URLs for each country's web-store. While the stores owned by INGKA all use the same URL design (e.g. *www.ikea.com/dk/da*), this is not the case for other franchisees (e.g. www.ikea.is or www.ikea.com.cy). So the base URL differs and we also need to obtain the 2 letter country and language codes. Since they are the official ISO-3166 ALPHA_2 and ISO-639-1 code respectively, premade packages can obtain the information necessary. The issue here is that the list we scraped contains non-official names for some countries (e.g. "Czech Republic" instead of "Czechia" or "Russia" instead of "Russian Federation"). This also can be solved with the packages used to obtain the country codes. While all countries just have one country code they can have multiple language codes (e.g. Belgium with three official languages). Here we choose to use the most common one.
For later use the ISO 4217 codes (codes of the national currencies e.g. "DKK") as well as the ISO-3166 ALPHA_3 (3 letter country codes e.g. "DNK") are obtained. To later differentiate between the ESM and the rest of the world we introduce a dummy, where a value of 1 indicates membership.

Using parts of this data we obtain the URLs by looping through the different possible URL options starting with the most common one and store the ones that give a "200" response status code.

[4]https://web.archive.org/web/20181223020957/http://franchisor.ikea.com/wp-content/uploads/2018/11/Franchisee-slide-29Nov2018.jpg
[5]https://en.wikipedia.org/wiki/List_of_countries_with_IKEA_stores#cite_note-:1-1

If any other code (e.g. "404) appears a new option is tested. Here we make sure that the loop does not get interrupted by timeouts or not found web pages. All of this information is then saved in one dataframe.
Holdings whose stores we exclude are Dairy Farm, House Market Group, Mapa, Miklatorg Group, Northern Birch and Sarton Group (12 countries out of the 53 we started, which accounts for roughly 9 percent of all stores) the only store from INGKA Holding that was excluded is Spain. These exclusions are made because the websites are built fundamentally different.

2.2 Building the Web Scraper

IKEA has a dynamic webpage where we need to click elements to be able to obtain the data we need. Since there is no option to view all products and prices at once, our best option was to iterate through categories within each country. We select nine categories: Sofas, Small Storage Organizers, Linen, Rugs, Dinnerware, Cookware, Lamps, Tables Desks and Beds. On each category page, we can obtain the first 24 products from the given category. To see more products we need to click a button that loads the next page. Because the dynamic nature of the webpage it is not possible to iterate through pages with the *requests* function, which leaves us with the *selenium* module, that we used to build the scraper.

As mentioned IKEA can be split into the big INGKA Holding Group and other franchisees. We saw that the setup of the national webpages is almost identical for the INGKA Holding Group countries, but has different setups in the other ones. Thus we need to create separate functions for the different franchisees.

For the INGKA Holding Group, we set up a function that takes a single URL for the country and a single category code as inputs. This initializes the ChromeDriver through the *selenium* module to the given category page in the given country. Here a cookie pop-up pops up, which shape, placement and existence vary across countries. This means that we, at least for some countries, have to accept (or decline) cookies to be able to locate the "next page" element. We locate the "accept cookies" element by its *xpath*, which we can use since it is the same for all countries, where cookies need to be clicked. Next, we need to know how many products there are in the category, and how many products there are on each page. We need this, to know how many times we should click on the "next page" element. The information is stored in one single string which we can clean for letters and store the total number of products and the total number per page. Because China and Japan read from right to left we need to make a condition that we need to collect the information from the opposite side of the string. Now we will locate the "next page" element which is done by the class name, except in China and the Netherlands where we instead use *xpath* and *css-selector* respectively. Then we tell the driver to scroll until the element is viewable and click it. For countries where we don't click cookies away, it then scrolls until the element is behind the pop-up and thus not clickable. We solve this by tasking the driver to scroll a bit further and then click the element. To be able to click the element multiple times, we create a function that repeats the process of clicking the "next page" element n times, where n is the total number of pages.

Now we have the full webpage with all products for the given category. We parse the webpage using BeautifulSoup and find all product container elements. We have to make a special condition for China because there the class name is different. Each product container contains information about price, name and product code. This means we can iterate through the product containers to obtain this information, and create a data frame. The function for the INGKA Holding Group then returns this data frame.

The functions for the other franchisees are made similarly, but we decided that it is easier to make separate functions, also for easier readability, for them since the design of their websites varies much more. So we made functions for the Al-Futtaim Group, Al-Homaizi Group and one combined for Al-Sulaiman and Ikano.

Each of the functions takes a single URL and a single category as input, but we wanted a function that could take a list of URLs and a list of categories as input, and return a single data frame. So we created a nested master function which takes lists as input and iterates through the URLs to determine which country it is, and which group the country is in. Then one of the functions described above runs through for a single category and returns a data frame. The latter function iterates this iteration for each category, so we end up with the full data frame. The function then stores the raw data frame and continues to the cleaning of the data, and returns the full, cleaned data frame. This function also generates the codes that in each sub-function are used to name the log file, documenting the scraping process. We decided to use the build-in logging mechanism of the ChromeDriver and produce one log file per country-category pair. This produces more files but makes it easier to find the log in question and re-run just the particular areas, where we might see problems. The log name includes the holding, the two-letter country code as well as the category code (e.g. "log_ikea_ingka_dk_bm003" for beds in Denmark)

We ran the functions in the jupyter notebook individually, not with the master functions, to make it easier to fix small mistakes and to not start all over again, because the scraping is a time-consuming process (we estimate it is about a day to run it front to back). The data we use was obtained in that way. However, to showcase that the code as presented in the notebook works we ran a proof of concept with the master function. The input for this were two categories and one country per holding/sub-function (with two countries for INGKA Holding, to showcase ESM and non-ESM).

2.3 Ethics and Data Collection

Since scraping is usually in a grey area, we made sure to look up the terms of use for the countries where we speak the languages well enough to understand them (Australia, Austria, Canada, Denmark, Germany, Norway, Spain, Sweden, Switzerland, United Kingdom and the US). Following them, we reached out to the ones that asked us to do so in their terms of use (e.g. United Kingdom, Switzerland and the US) to ask for permission. However, probably due to time and the current situation none of them answered us before the hand-in date of our project so we just went ahead and scraped the pages.

The general rule for IKEA seems to be, that all the content on their pages is protected by their copyright, from trademarked names via front-end code to products descriptions. The download of contents for private use is allowed and also its distribution, as long as there is no profit orientation. The reproduction of this information outside of personal use is not allowed.

There is only one of the countries' terms and conditions we checked that explicitly stated "You may not use any robot, spider, another automatic device, or manual process to monitor, copy or scrape any of our web pages or the content contained herein, without the prior express written consent from an authorized executive of IKEA".[6] We requested written consent from IKEA US.

We are not sure if we do violate the terms of service (at least the ones we were able to read), except for the ones from the US, where we are positive that we do. Although we are not sure if our use of the websites is compliant with the terms and conditions, we think we are fine since we do not have the intend to make profit from it or violate the copyright. We also made sure to save the data on local hard drives and just display aggregated data in our paper.

We still went ahead with also scraping the US page because we think it is an important country in the world economy and the second biggest market for IKEA. Also since we motivate this index with the Big Mac Index that takes the US prices and the USD as its baseline we wanted to see how they compare.

We made sure, that our scraping would not cause harm to the websites by including *time.sleep()* between loops and requests and also scraped by category, not by country (scraped the products for one category for country A and then scraped the same category for country B, before returning to country A for the next category) to spread out the strain on the servers. For all our requests we tried to include headers stating the purpose of the requests and contact information. Wikipedia has no problem with being scraped and also provides an API.

[6]IKEA US, Use of Service, available at https://www.ikea.com/us/en/customer-service/terms-conditions/

3 Data Cleaning and Methodology

IKEA is operating in 53 countries worldwide, and we scraped data from 40 countries. We excluded 13 countries, from different franchisees, in the process due to a very different design of the websites and -pages. To construct the index in a comparable way to the Big Mac Index, we used the currencies used in the latest version of the Big Mac Index. The Big Mac Index is not computed for all countries of the world, and also not in each of the 40 countries we were able to scrape for data. So we drop 2 countries which are not in the Big Mac Index, which leaves us with 38 countries. We can identify the products by their product codes in the process of computing the index. Some countries, however, use different product codes than the majority of the IKEA country stores. Since the product codes are the only way to identify the products, we drop 8 countries where the product codes are different. Product names can not be used to identify the product, because the same name is used for all products in that series, which might vary in size, color and price.

The scraped information on IKEA products was merged with a data frame from the GitHub repository containing the information for computing the Big Mac Index [7]. This repository also contained exchange rates and nominal GDP per capita in US-dollars for different dates, but we selected the last observations to avoid time inconsistencies, that is: 2020-07-01. After some manipulations and merging of data frames, we compute the indices. Despite the official Big Mac Index being computed relative to US prices, we compute it relative to Denmark's prices. There is not a specific reason to choose Denmark as the reference country, but it could be important to use a reference country within the European free trade area as this could affect significantly prices for IKEA products.

3.1 The Big Mac Index

The Big Mac Index is obtained as follows:

$$\beta^i = \frac{P^i_{dkk} - P^{DK}_{dkk}}{P^{DK}_{dkk}}$$

- Big Mac Index at country i: β^i
- Price of Big Mac in country i in DKK: P^i_{DKK}
- Price of Big Mac in Denmark in DKK: P^{DK}_{DKK}

It represents how much a Big-Mac costs in country i relative to Denmark, in Danish prices. Assuming the price-income relationship holds in a monotonic increasing way, we expect purchasing power to increase with production.

3.2 The IKEA Index

Similarly, we build an IKEA Index for each product j on each country:

$$\lambda^{i,j} = \frac{P^{i,j}_{DKK} - P^{DK,j}_{DKK}}{P^{DK,j}_{DKK}}$$

where $\lambda_{i,j}$ represents the IKEA Index for product j in country i. Then, we obtain a country specific index (*IKEA_Index_DK*) by taking the average of λ^i where N is the number of product codes that each country shares with Denmark.

$$\Lambda^i = \frac{1}{N}\sum_{j=0}^{N} \lambda^{i,j}$$

[7] https://github.com/TheEconomist/big-mac-data

4 Results

The indices we use represent price levels. Using the Big Mac Index, if the price of a Big Mac is 21 percent higher in Norway than in Denmark, according to PPP, Norwegian Krone would have to be a 21 percent overvalued over Danish Kroner (given that Denmark is our reference country for indices computations). According to the IKEA Index, IKEA products are on average a 7 percent more expensive in Norway compared to Denmark, and thereby Norway's currency would be 7 percent overvalued over Denmark's. If you find deviations between current valuations and theoretically predicted valuations there is an arbitrage opportunity for currency exchange that is supposed to be profitable in the long run.

However the index has limitations:

> *"The cost of a burger depends partly on non-tradable inputs, such as rent and wages, which are higher in the rich countries on the fringes of the euro zone. So the price of a meal may not be a good guide to how competitive a country is in markets for tradable goods"* The Economist 2018

For that reason, the IKEA Index could be insightful, as labor input costs are lower for each item, given that most goods are produced at countries with low labor costs and then transported to be sold. This implies that the cost of IKEA products also includes transportation costs, and maybe import tariffs (and other country-specific taxes). However, these transport costs are very likely smaller than the labor costs gap. If the transport cost is larger than the labor cost, the product will be produced in that territory instead of being imported from somewhere else, in an attempt to maximize the firm's profits.

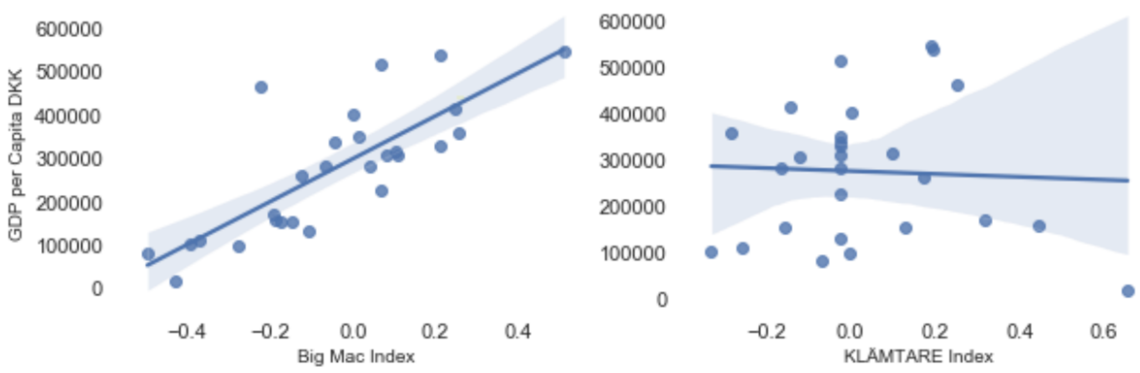
We use GDP as a proxy for purchasing power. This measure has limitations, as income distribution, country-specific regulations and consumer preferences can significantly undermine its consistency as an indicator. However, it tends to serve as a good proxy.

4.1 Product-specific IKEA Index

Initially, we obtain the index for 'KLÄMTARE', one of the most popular products in terms of availability across countries. Then we compare it to the Big Mac Index:

In Figure 1 we observe that OLS regressions for each index as exogenous variable and GDP as endogenous show that while the Big Mac Index nicely matches GDP, the KLÄMTARE Index seems to be uncorrelated. Heterogeneity across regions and products forces us to look at the averaged IKEA

Figure 1: OLS regression of GDP on the Big Mac Index (left) and the IKEA Index (right) for the product: KLÄMTARE

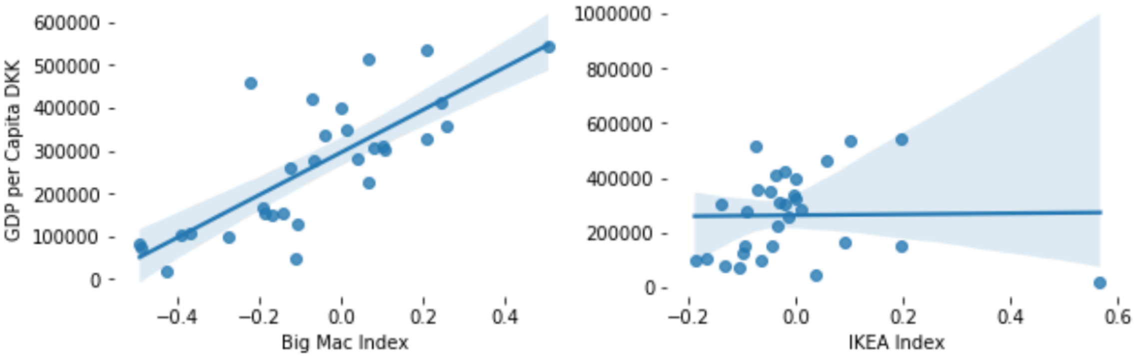


Index instead, where all product indices have been taken into account and we expect a convergence that would explain better purchasing power at a regional level.

4.2 Averaged IKEA Index

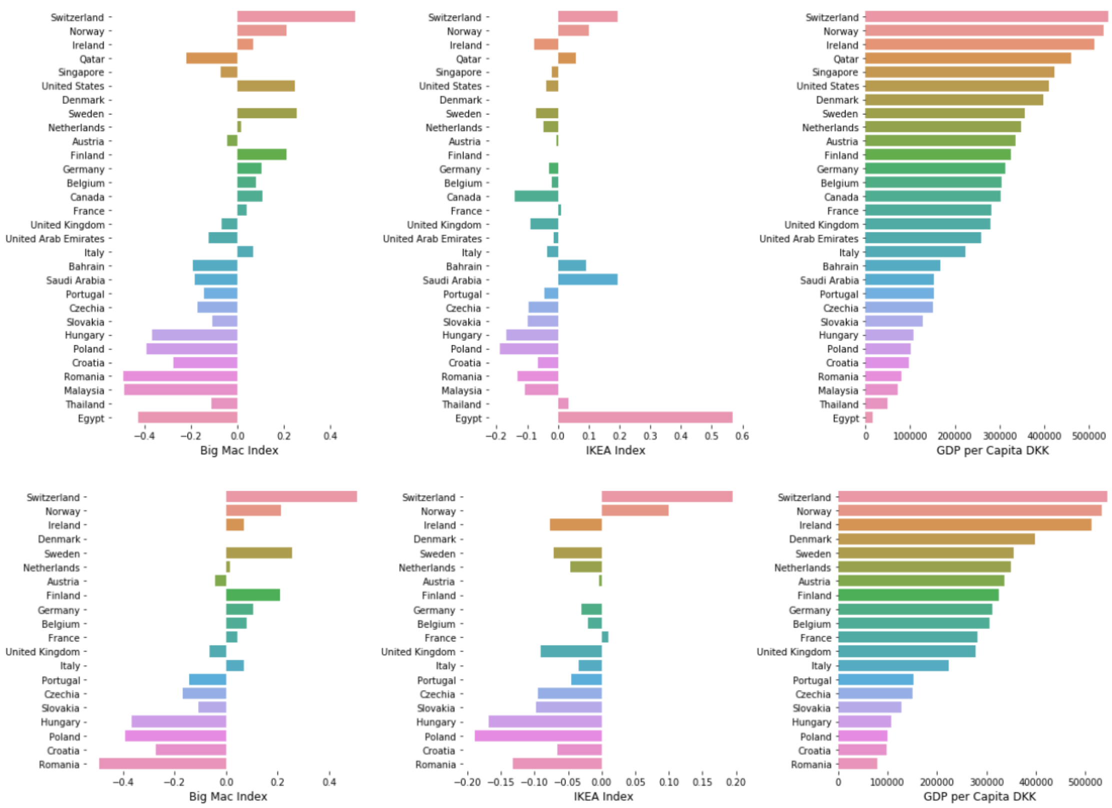
Each averaged index seems to converge in Figure 2, drawing a clearer pattern than the product-specific index, however, the conclusion seems to be the same: No relationship between both variables.

Figure 2: OLS regression of GDP on the Big Mac Index (left) and the average IKEA index for each country (right)



Although, when we look at Figure 3, we observe which countries deviate most from the expected index values. There seems to be a pattern even though countries such as Egypt, Thailand or Saudi Arabia to deviate from this. Now we separate the countries on those participating in the European

Figure 3: Indices for countries sorted by GDP. The 2nd row of graphs only contain countries in the European Single Market (ESM)

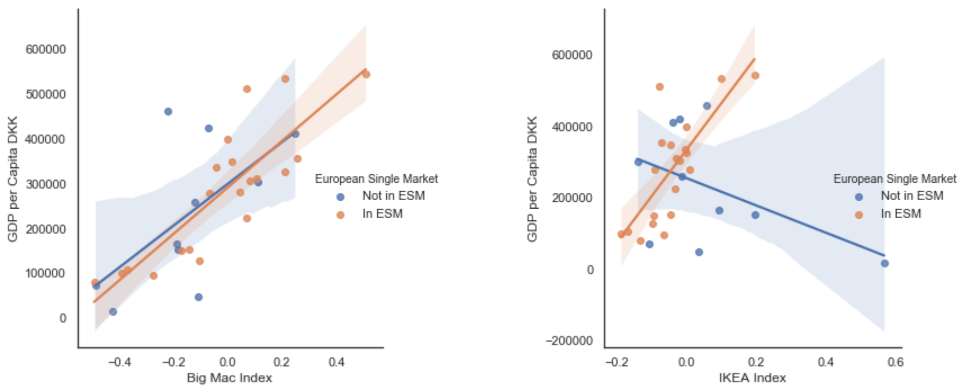


Single Market, and those that do not. In Figures 4 it becomes clear that, while the Big Mac Index improvement comes mainly in terms of lower variance, the IKEA Index indices we find a completely different relationship.

There is a strong significant positive relationship between the index and GDP. On the other hand,

Figure 4: Relationship between indices and GDP

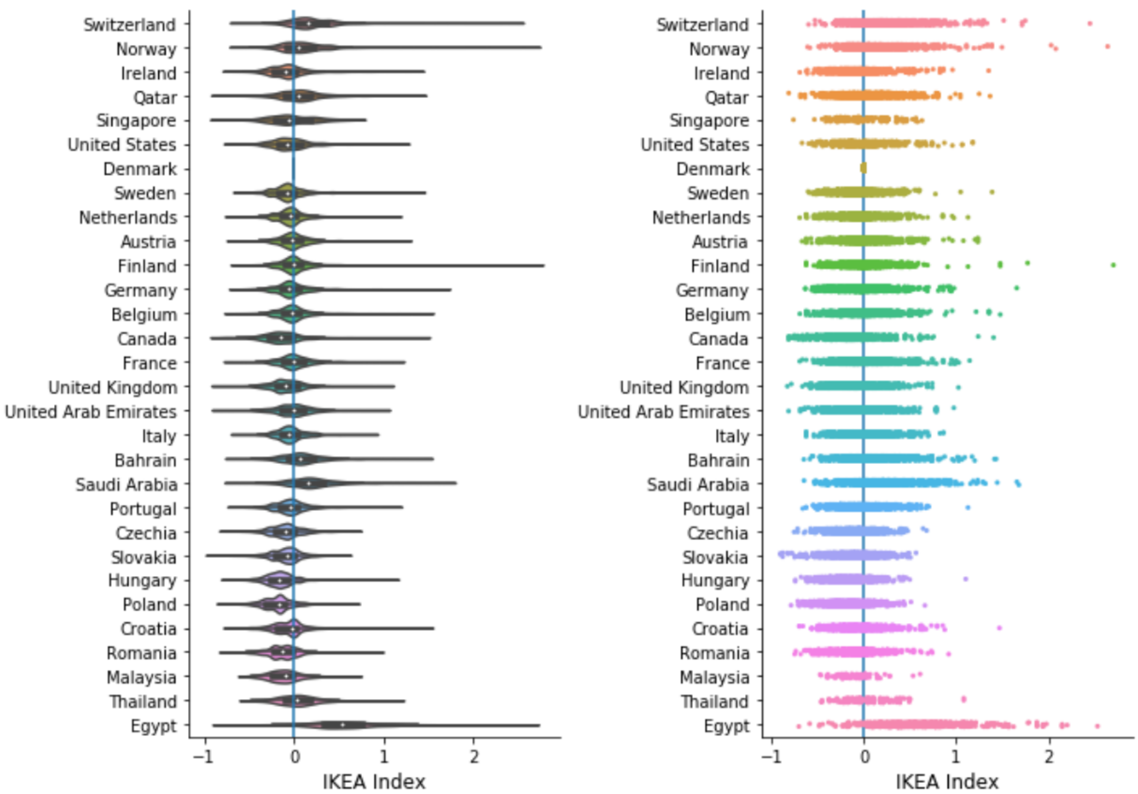
(a) Big-Mac Index (b) IKEA Index



the relationship is not that clear for outer countries and is especially driven by a few values that seem to be more extreme.

The violin plot in Figure 5 (left) visualizes the distribution of product-specific-IKEA-indices in each country. The distribution functions tend to be right-skewed, caused by a few extreme outliers on the right tail, meaning that for a few products, prices vary significantly across regions and these products drive up the averaged IKEA Index. The violin plot does not show this as well as the strip plot, but it gives a better visualization around the average.

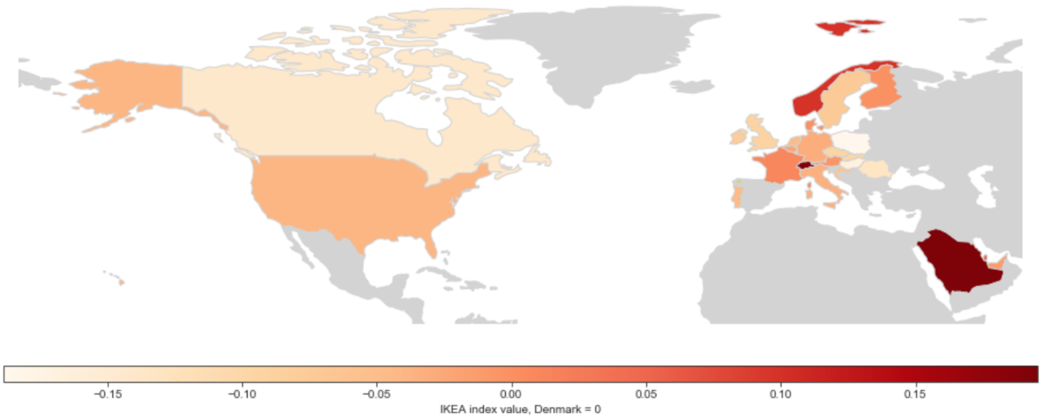
Figure 5: Distribution of product-specific IKEA indices for each country



4.3 Maps

In Figure 6, we have plotted the IKEA Index on a heat map for all the countries in the sample. The scale goes from -0.15 to 0.15, indicating that the price range varies 15 percent from the prices in Denmark. We see that the prices are highest in Switzerland, Saudi Arabia and Norway and lowest in the Eastern European countries, we excluded Egypt from this figure as the prices are more than 50 percent higher than the danish ones and thereby disturbing the pictures variation.

Figure 6: IKEA Index heat-map



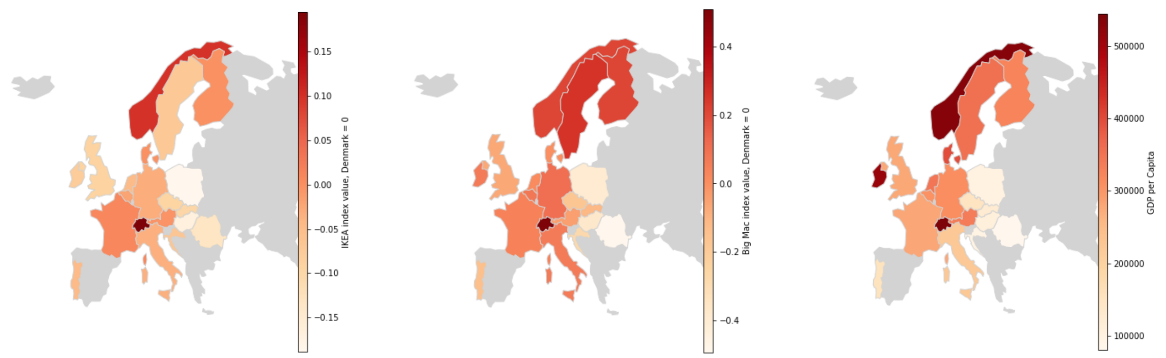
Note: Egypt is excluded

We now extract the European countries to further analysis since they are more comparable. The map on the left in Figure 7 is the IKEA Index (a), the middle the Big Mac Index (b) and on the right is GDP per capita (c).

From a visual inspection, it looks as there could be a correlation between the IKEA Index and GDP per capita, as the countries with high GDP per capita also seems to have higher IKEA prices. The exception here might be Ireland since the GDP per capita is relatively high. This could be explained by the low company tax in Ireland, which somehow disconnects GDP from income, and therefore skews the measure. We see that there are some differences in how the IKEA Index and the Big Mac Index catches the prices. Most noticeable is the fact that the price range variance is lower for the IKEA Index. This corresponds with theory since we include more products in our basket of goods, the price range variation should decrease.

Figure 7: Heat-maps

(a) IKEA Index (b) Big Mac Index (c) GDP per capita



4.4 Analysing product indices for each category and OLS

We now observe how the Index regression on GDP per capita performs for each category of IKEA products. These are Sofas, storage, linen, rugs, dinnerware, cookware, lamps, tables and beds. Our sample of non-ESM countries is too small to find patterns, if there are any, as plots show insignificant relationships with negatively sloped correlation. Nevertheless, the positive significant linear relationship can be found in the ESM countries for all the available categories. We find higher variance for sofas, linen and rugs.

We regress *GDP per capita* in millions Danish Kroner with the explanatory variables, Λ^i, *ESM*, and Λ^i and *ESM* multiplied, where Λ^i was the IKEA Index for country i.

$$y = \beta_1 \cdot \Lambda^i + \beta_2 \cdot ESM + \beta_3 \cdot \Lambda^i \cdot ESM$$

The ESM dummy variable tells us whether a country belongs to the European Single Market (ESM) or not, and when we multiply it with the index (Λ^i) we have a variable that explains the impact of the IKEA Index in ESM countries. We run this regression for each category and also for the full sample, cf. Table 2. Throughout the regressions, the dummy is significant at 1 percent level for all categories. This captures the higher GDP per capita for countries within the ESM. The IKEA Index variable for non-ESM countries is insignificant for all categories and for the full index as well. The β_3 varies in significance among categories. For linen, rugs and lamps it is insignificant. This can be explained because the direction of the regression is based on just a few values, as most observations are distributed around zero. For sofas, tables, and beds β_3 is positively significant at the 10 percent level, and for storage, dinnerware and cookware β_3 is positively significant at the 5 percent level. The β_3 for the full index is positively significant at the 5 percent level, which indicates that the price level in ESM countries correlates positively with GDP per capita in that country. Figure 8 in the Appendix plots these relationships among categories.

Table 2: IKEA indices for each product category for countries in and out of the European Single Market

	Sofas	Storage	Linen	Rugs	Dinnerware
β_1	-0.15	-0.07	0.20	0.05	-0.15
	(0.21)	(0.27)	(0.24)	(0.34)	(0.30)
β_2	0.29***	0.36***	0.28***	0.35***	0.38***
	(0.04)	(0.05)	(0.04)	(0.06)	(0.05)
β_3	1.20*	1.20**	0.60	1.30	1.15**
	(0.62)	(0.48)	(0.50)	(0.76)	(0.45)

Standard errors in parentheses. * p<.1, ** p<.05, ***p<.01

	Cookware	Lamps	Tables	Beds	Full index
β_1	-0.16	0.21	0.20	0.12	0.01
	(0.29)	(0.34)	(0.26)	(0.30)	(0.30)
β_2	0.37***	0.28***	0.31***	0.32***	0.34***
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
β_3	1.37**	0.90	1.06*	1.28*	1.29**
	(0.55)	(0.54)	(0.54)	(0.73)	(0.58)

Standard errors in parentheses. * p<.1, ** p<.05, ***p<.01

5 Discussion

5.1 Purchasing Power Parity

The Purchasing Power Parity (PPP) is the theory, that good in one country has the same price in other countries when adjusting for exchange rates. So when dividing 2 prices, for country A and country B, for the same product, you have a measure PPP:

$$PPP = p_A/p_B$$

This is an alternative to market exchange rates and is sometimes used instead of the market exchange rate to calculate a comparable GDP measure across countries. The World Bank has collected a basket of goods, which intentions it is to cover all prices in society. With the basket of goods, the World Bank is able to compute the overall PPP and PPP for different categories. One of the categories computed is "Furnishing, household equipment and routine household maintenance"[8] which we think should be comparable to a PPP computed with the IKEA data. We calculate the IKEA PPP with the data we have in our dataframe, and collect the World Bank PPP, for that specific category, to compare them. We run a simple OLS regression to see how well our data fits on the World Banks.

$$PPP_{WorldBank} = 0.79^{***} \cdot PPP_{IKEA}$$

We find a coefficient of 0.79, which is significant at the 1 percent level. This indicates that our data is fairly accurate and a good proxy for the World Bank's PPP.

5.2 Human Development Index

We could have also looked at how well our index can be used to look at developmental aspects. Maybe developing countries, that orientate themselves in the direction of western societies regard products like IKEA furniture as "western society good". This might change the value attributed to the product in comparison to the products of the home market. This could go so far, that in the extreme case it might become a Giffen good.
Therefore it could be interesting to look at the Human Development Index (HDI) and see how it relates to our IKEA Index.

5.3 Dropping of Countries and Regions

To get a better picture it would be nice to find a way to scrape the pages from the franchisees we did exclude or keep some of the countries we scraped, that use different product codes. We did not find a way to connect them.

[8]https://databank.worldbank.org/source/icp-2017

6 Conclusion

The Big Mac Index is supposed to represent price levels under the PPP hypothesis. Here, GDP per capita is being used as a proxy for purchasing power, under the assumption that countries with low GDP per capita have less available income and a lower internal demand and willingness to pay, keeping prices low. This means that the price-income relation is monotonically increasing.

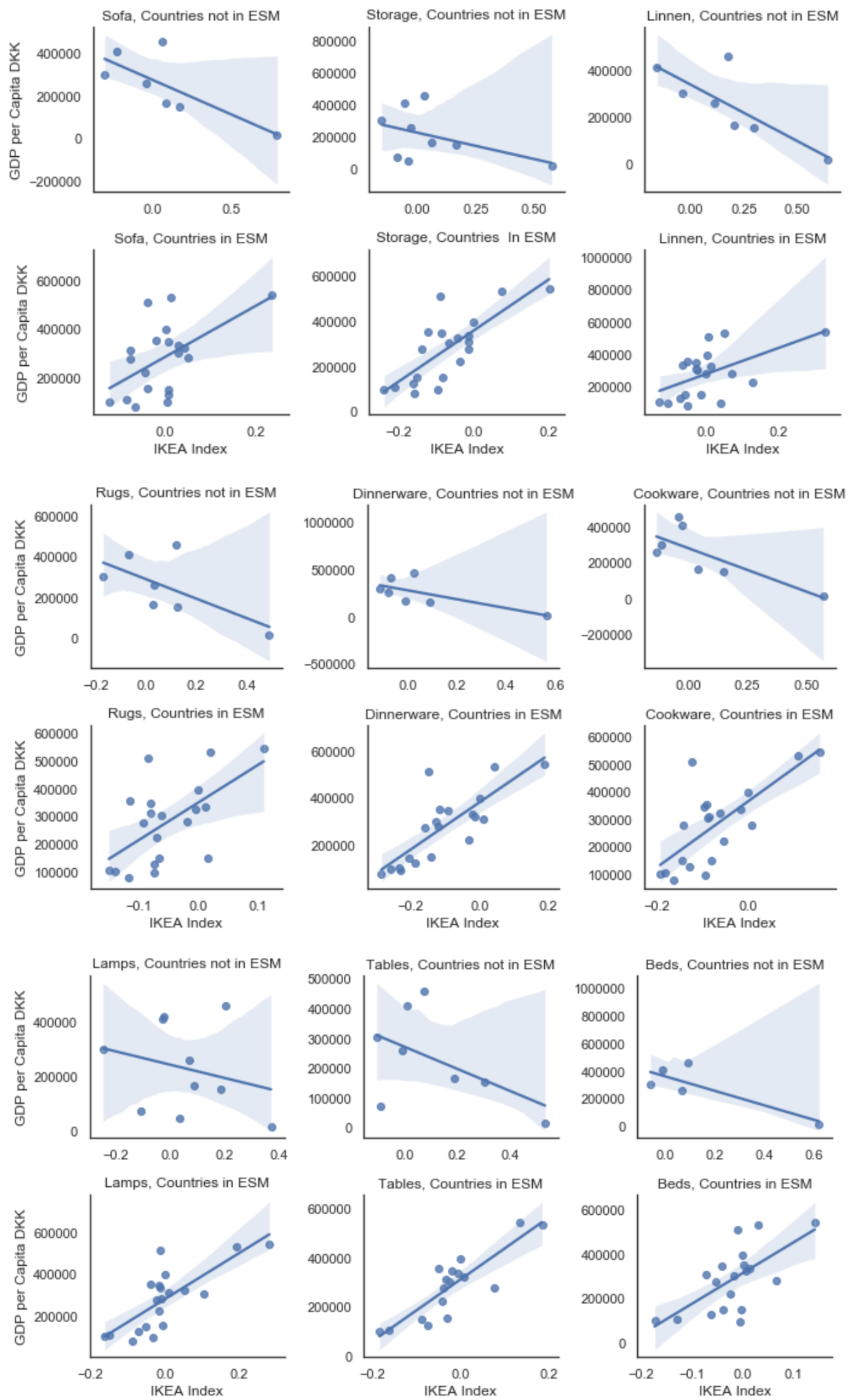
The Big Mac Index seems to be a better predictor of GDP per capita than the IKEA Index, but this difference is mainly due to non-ESM countries. The IKEA Index performs well in ESM countries, but correlation seems to be negative, although not significant, for non-ESM countries. This pattern is repeated across product categories, with a few exceptions (lamps, linen and rugs). For linen, rugs and lamps the coefficient on the IKEA Index is insignificant, which could be explained by the distribution of the observations in these three categories. By visual inspection, we see that most observations are distributed around zero, and given the small sample size, significance levels might vary after including more countries. Lastly, we find that our data is a good proxy for the World Bank's PPP, which we see as a quality mark of our data.

These results are consistent with those in Hassan 2016, that finds out that the price-income relationship turns negative across low-income countries, and is therefore non-monotonic.

We conclude, that the IKEA data is a good indicator of PPP, since the PPP of IKEA products can explain 79 percent of the calculated PPP by the World Bank. The IKEA data is a good indicator for price levels, when observations are for countries in Europe, but does not explain the price levels in countries outside Europe.

7 Appendix

Figure 8: IKEA indices for each product category for countries in and out of the European Single Market



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